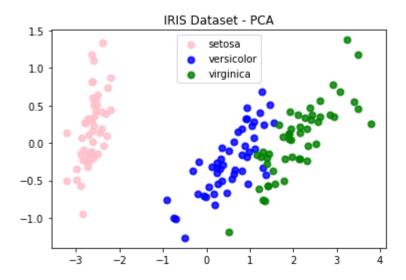
```
In [52]: 
X = iris.data
y = iris.target
target_names = iris.target_names
colors = ['pink', 'blue', 'green']
lw = 2
```

```
In [53]:  ##Question 1
pca = PCA(n_components=2)
X_r = pca.fit(X).transform(X)
print('First three components variance ratio: %s' % str(pca.explained_variance)
```

First three components variance ratio: [0.92461872 0.05306648]

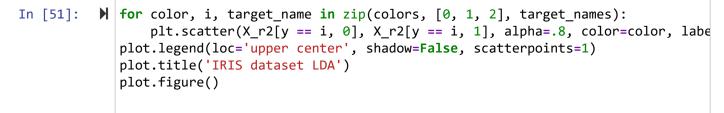
Out[54]: <Figure size 432x288 with 0 Axes>



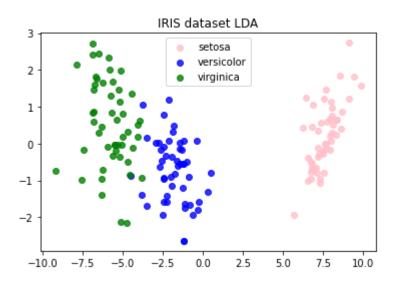
<Figure size 432x288 with 0 Axes>

```
In [41]: ##Question 2: I have decided to use Linear Discriminant Analysis

lda = LDA(n_components=2)
X_r2 = lda.fit(X, y).transform(X)
print('explained variance ratio (first two components): %s'%str(lda.explained
explained variance ratio (first two components): [0.9912126 0.0087874]
```



Out[51]: <Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

## #QUESTION 3

- 1. In this Assignment I have made use of PCA like mentioned in the question. The other analysis I have made use of is LDA. The variance for both types has been displayed. The variability and range between the 2 types vary a lot. We can clearly see that LDA is better. We come to this conclusion because we get more information from LDA than PCA.
- 2. From my observation I can say that LDA is better. I say this because, in the PCA graph we can see that versicolor (blue) and virginica (green) are very closely packed. But using LDA we can see that they are more distinguished and clearer.
- 3. We can note that PCA does not take labels. Unlike PCA, LDA considers labels. In this model since we make use of labels using LDA is a better option. It is also noteworthy that PCA is unsupervised and LDA is supervised. PCA as a technique that finds the directions of maximal variance and LDA attempts to find a feature subspace that maximizes class separability.

Reference: <a href="https://sebastianraschka.com/faq/docs/lda-vs-pca.html">https://sebastianraschka.com/faq/docs/lda-vs-pca.html</a>